Using Wearable Inertial Sensors to Compare Different Versions of the Dual Task Paradigm during Walking

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ABSTRACT
The dual task paradigm (DTP), where performance of a walking task co-occurs with a cognitive task to assess performance decrement, has been controversially mooted as a more suitable task to test safety from falls in outdoor and urban environments than simple walking in a hospital corridor. There are a variety of different cognitive tasks that have been used in the DTP, and we wanted to assess the use of a secondary task that requires mental tracking (the alternate letter alphabet task) against a more automatic working memory task (counting backward by ones). In this study we validated the x-io x-IMU wearable inertial sensors, used them to record healthy walking, and then used dynamic time warping to assess the elements of the gait cycle. In the timed 25 foot walk (T25FW) the alternate letter alphabet task lengthened the stride time significantly compared to ordinary walking, while counting backward did not. We conclude that adding a mental tracking task in a DTP will elicit performance decrement in healthy volunteers.

Author Keywords
MEMS; accelerometer; accelerometry; xio; x-io; xIMU; gyroscope; T25FW; ambulatory; ambulation; inertial.

ACM CLASSIFICATION KEYWORDS
HCI design and evaluation methods: Laboratory experiments.

General Terms
Human Factors; Affective computing; Measurement.

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INTRODUCTION

Importance of the Dual Task to Cognitive Ergonomics

In human factors and cognitive ergonomics, the risk of diminished performance due to increased mental workload has given rise to the multiple resource theory to explain why combining some tasks causes performance decrement, while other combinations do not [36]. For healthcare professionals the dual task paradigm is a way of explicitly testing how much cognitive load leads to walking performance decrement in the frail, the aged, and neurological patients. Combining walking with a cognitive task may be a surrogate for risk from falls and disability for individuals who would otherwise be confident walkers in an obstacle-free hospital corridor [7; 14; 34; 35]. However, this has become controversial because the association between marginal performance decrement (the dual task cost) and risk of falls has not been shown consistently [37; 18; 19]. The most recent guidelines for dual task tests of ambulation, which allow for tasks of varying difficulty, are outdated need updating [11].

Uses and Types of Dual Task Paradigm in Walking

In addition to predicting safety, dual task paradigms are used to detect cognitive motor interference [23]. For neurological patients with ambulatory disorders, walking in obstacle-rich environments (e.g. in shops, crossing the street) is both confusing and dangerous, to the point where patients may deliberately minimise their activities of daily living [22]. A dual task paradigm may partially reproduce the cognitive demands of walking among obstacles and moving objects, whilst remaining in a controlled environment.

Most dual tasks for walking involve speaking, and may include word production tasks (objects beginning with the letter "A"), or various counting backward tasks (by ones, tens, fives, threes, and sevens). Dual task effects are dependent on both the type of mobility task and on the difficulty of the attention demanding task. When the cognitive task is relatively simple, more attention resources are prioritised to complex mobility tasks (e.g., walking at fast speed) [24]. Dual-task effects on ambulation are significantly greater when paired with a verbal fluency task, compared with a working memory or visuospatial reaction time task [26]. The alternate letter alphabet task, where every other letter of the Latin alphabet is spoken (N,P,R,T, etc.), has been recommended as a possible dual task for standardisation in the clinic, and it is known that the task is more decremental when the task starts in the middle of the alphabet rather than the beginning (i.e. starting at "M" rather than at "A") [8].

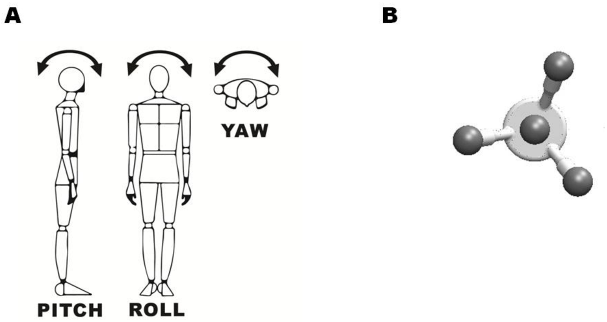

Figure 1. Methods for determination of angle directionality. Panel A shows the approximate directions of pitch, roll and yaw (depending on precise sensor stability) as we describe in this study. Pitch is nominally rotation around the medio-lateral axis (i.e., within the sagittal plane), roll is nominally rotation around the dorso-ventral axis (i.e., within the coronal plane), and yaw is nominally rotation around the vertical (superior-inferior) axis (i.e., within the transverse plane). Panel B shows an example of the three-way reflective markers used to derive precise attitudes for the Vicon experiments. Each reflective ball is 9 mm in diameter, with the assembly size being 5 cm in diameter [21].

Wearable Inertial Sensors to Measure Ambulation

Measuring performance is essential in ergonomics for assessing energy expenditure and efficiency, and in clinical practise for assessing ambulatory disability. Basic assessments of walking are based around timing of short walks (e.g. the timed 25 foot walk, T25FW), or the distance travelled during longer times (e.g. the six minute walk, 6MW, for assessing fatigue). More detailed measurements of gait performance can be gathered -- including parameters for times, distance, linear acceleration, angular velocity, frequency, and complexity (e.g. entropy and fractal dimension) -- using force plates, goniometers, instrumented walkways, GPS, pressure sensors, opto-electronic motion capture (e.g. Vicon), wearable inertial sensors, and other technologies. Wearable sensors provide a reasonable compromise between cost, convenience and measurement detail; they can provide excellent resolution for temporal variables, angular velocities, angles (when still or very slow) and acceleration, while they rely on complex recalculations and pattern recognition for calculating distances (e.g. dead reckoning) and precise angles.

Our goal was to compare the effect on stride time (the reciprocal of walking pace) of a) the dual task with the alternate letter alphabet against b) the dual task of counting backward by ones, which has a limited effect on gait in healthy young people [5].

METHODS

Experimental Volunteers

In study one (validation), four male healthy participants (age range 21-27) were asked to perform a range of walking tasks in a large Vicon laboratory (18 cameras) while wearing both 7 inertial sensors and a set of passive reflective markers for Vicon. In study two (dual task test), fifteen healthy participants (age 34.1 ± 8.9, 5 females) were tested on the effects of adding different kinds of cognitive tasks to a walking task. All studies were carried out in accordance with the approval of the local ethics committee, with written informed consent obtained from all subjects in accordance with the Declaration of Helsinki. Participants were recruited via email to the university community and received £20 for their travel and/or time.

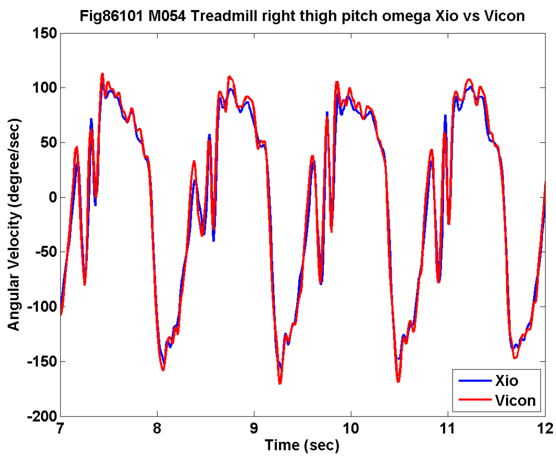

Figure 2. Representative data for validation of the x-io sensors vs. the Vicon system. The data shows the pitch angular velocity of the thigh (with respect to the ground) during a treadmill walk at nominal 4 km/hr. The x-io sensor, mounted at the lateral aspect of the lower thigh, provides the unfiltered gyro readings around the z axis, resampled from 128 to 100 Hz (blue, underlaid). The Vicon thigh angle data (red, overlaid) is low pass filtered (15 Hz).

Protocol

After receiving participant information and providing consent, participants were asked to wear running shoes we provided (Lonsdale Leyton Men's trainers in their size) and 7 sensors located on: left and right ankles (just above the lateral malleoli), left and right thigh (lateral aspect, 10 cm above knee), left and right shoes (lateral aspect, at the position of the cuboid), and the lumbar spine (at the level of L3). Body sensors were held in place with elasticated fabric bands with Velcro on both the fabric and the sensor; shoe sensors were placed directly onto the shoes, which had dual lock strips (3M™ Dual Lock™ SJ3560) affixed directly on them. To prevent the thigh sensors from slipping (due to the changes of the thigh diameter), gaffer tape was sometimes used to affix the elasticated fabric to the participants' trousers. Backwards counting started from 990, and numbers were diminished from one task to the next (no repetition). The alternate alphabet task started on "M" the first time, and on "N" the second time. At the end of all walking tasks, the participants filled in a questionnaire with ratings scales from 0 ("Not at All") to 100 ("Extremely"), asking for each dual task how difficult they found it, and how much they thought it affected their walking.

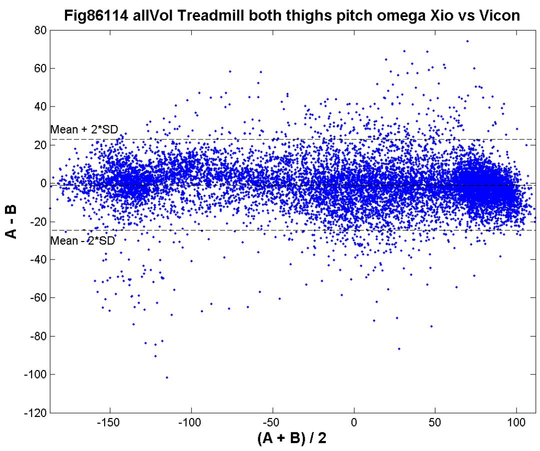

Figure 3. Bland-Altman comparison of pitch angular velocities determined by Vicon to those determined by x-io sensors. Four healthy male volunteers were tested on a treadmill walk at a comfortable speed

Sensors

The sensor nodes used were x-IMU by X-io (Bristol, UK), with 3 dimensions each of accelerometry, gyroscopy and magnetometry. These sensors are factory calibrated for gravitational acceleration (accelerometers) and angular momentum (gyroscopes), and they incorporate onboard algorithms for estimation of heading and quaternions [15; 17]. Data from all nine Micro Electro-Mechanical Sensors (MEMS) in each x-IMU node were recorded at 128 Hz onto the onboard 32 GB micro SD cards (SanDisk Ultra Micro) with the sensors' blue tooth transmission turned off (to extend battery charge). Time alignments between sensors and with other measurements and video tapes were performed using a manual synchronization strategy. Directions used (i.e. pitch, roll and yaw) are shown in Figure 1 (panel A).

Binary file sensor data were transferred to a Windows 7 computer, and the binary files were converted into csv files using the manufacturer's provided GUI. The csv files were read into Matlab, and all sensor data was aligned (based on the synchronization signals at the beginning and end of the experiment) using a purpose-made script; timing differences between sensors were interpolated linearly – at no point did the original sensor acquisition data differ by more than 50 milliseconds between sensors (over the course of 90 minutes of acquisition).

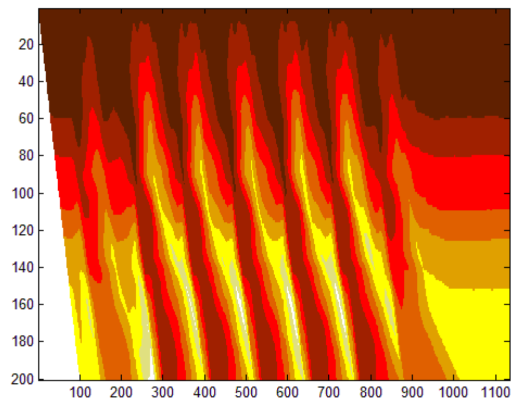

Figure 4. Representative accumulated cost matrix for dynamic time warping. The x-axis represents the sample number of the data query (128 Hz), from the right foot of a participant (M071) walking the T25FW during the alphabet task. The Y axis represents the sample number of the stride template. The data being matched is for scaled (-1 to 1) pitch angular velocity data. In this pseudo-colour image, white and yellow are high cost (poor matches), while darker colours (e.g. brown and red) represent low cost matches.

Sensor Validation with Vicon Opto-electronic System

These sensors have been previously validated for rotational accuracy [33], and our team also validated their accuracy during walking gait (particularly with our filtering and synchronisations) by two methods using values derived by a Vicon 18 camera opto-electronic system (Vicon, Oxford, UK) , which is capable of resolution to < 1 mm, in a gait laboratory [20]. In brief, we tested the x-io sensors' raw angular velocity data in the pitch direction from the thigh against the differential of simultaneously recorded Vicon angle positions for the thigh segment. We also compared initial contact (heel strike) from the wearable sensors on the shanks/ankles to heel strike calculations from the Vicon system. The Vicon motion capture system collected kinematic data at 100 Hz. Marker coordinate data were processed using a low-pass Butterworth filter with a cut-off frequency of 6 Hz.

Four healthy volunteers performed walking tasks while recording simultaneously with the Vicon and with the sensors. Reflective markers (9mm) were attached to anatomical landmarks on the pelvis and lower limbs using double sided adhesive tape. This marker configuration was in accordance with the Istituti Ortopedici Rizzoli model [12]. To track segment movement, a 3D cluster was embedded into the coordinate system of each respective segment. Each 3D cluster (Figure 1, panel B) was built by a 3D printer using ABS thermoplastic material (Dimension bst 1200es, Stratasys, Germany). Information on the technical frame of a 3D cluster is reported elsewhere [21]. Volunteers each performed three types of walking task: a fast over-ground walk (at preferred walking speed, velocity > 1.0 m/s), a slow over-ground walk (velocity < 0.8 m/s), and a treadmill walk at a preferred speed (nominally 4.0 km per hour).

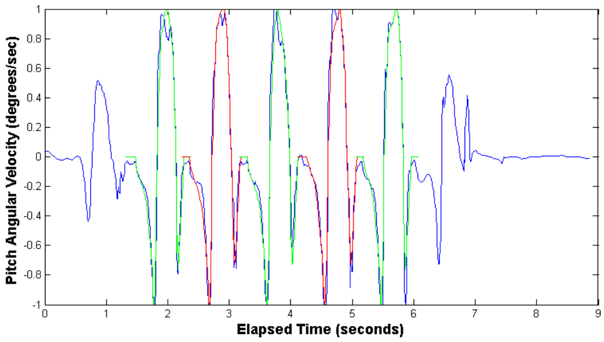

Figure 5. Representative data of template overlays from dynamic time warping. The blue trace is linearly scaled pitch angular velocity data (-1 to 1) from the same data as in Figure 4. The red and green overlay traces are identical template traces (coloured differently for clarity) that have been scaled and warped to fit exactly, allowing for the recognition of initial contact (heel strike) time. The parts of the blue trace without overlays are the first walking step and the final walking step (after completing the task) that were not recognised by DTW.

Analysis and Dynamic Time Warping

For validated gait temporal features, we compared heel strike and toe off times from the Vicon system to the times derived from two x-IMU sensors placed on the lateral shanks placed 2 cm above the lateral malleolus using dynamic time warping. In the sensor data, the steps were recognized by a pattern recognition algorithm based on dynamic time warping (strict form, 1:2 to 2:1) based on code from audio analysis in Matlab [4; 30]. The angular rotation signals of the pitch angle of the feet (gyro Z axis) were fitted to a template pattern that is characteristic of taking a step during walking; before pattern recognition, both template and query signal were linearly scaled from -1 to 1, where zero values were maintained (i.e. there was a positive scale and a separate negative scale). The pattern fitting algorithm provided a toe-off and heel-strike time for each step, accurate to 14 ms. Stride time (the reciprocal of cadence) was the time between two successive heel-strikes of the same foot.

Statistics

All statistics were calculated in Matlab. The distributions of walking were normally distributed, so comparisons were made using the repeated measures ANOVA. The distributions of the subjective ratings were not normal, so non-parametric statistics were used (resulting in P values for the distributions) with a Wilcoxon Signed Rank test.

RESULTS

Validation of Sensors

The x-IMU sensors are calibrated at the factory by an automated 3-DOF process on a gimbal [16]. To test the validity of the measures derived from them, we compared step-by-step measurements of gait metrics as measured by an 18-camera opto-electronic system (Vicon) vs. the sensor-derived metrics (from the ankle and thigh) in four healthy volunteers while walking. Each volunteer performed 3 walking tasks (see methods).

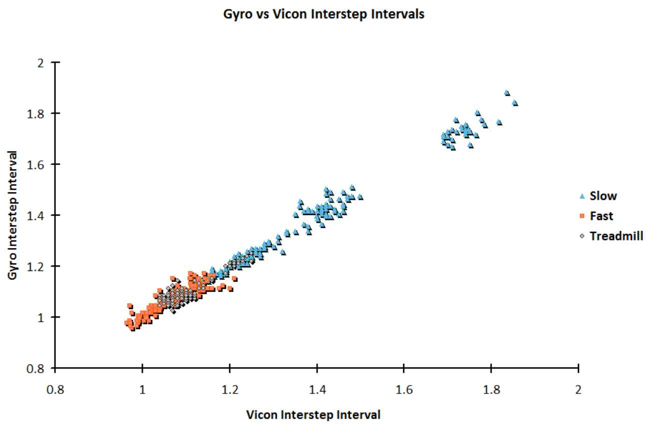

Figure 6. Comparison of stride time values (time between heel-strike) determined by Vicon to those determined by sensors with dynamic time warping. Four healthy male volunteers were tested using three different tasks: a slow walk overground, a fast walk overground, and a treadmill walk at a comfortable speed.

To validate the angular velocity data, the four volunteers from study one walked at a constant rate on a treadmill for over 20 seconds. After resampling the raw sensor pitch gyroscope data to the sampling rate of the Vicon, the left thigh pitch angle of the Vicon data was differentiated to provide an angular velocity, and the data showed excellent correspondence when overlaid (Figure 2); in this figure, the positive plateaus represent stance phase, while the negative peaks represent swing phase.

All treadmill data from participants were combined and compared (MEMS sensor vs Vicon) using a Bland Altman plot (Figure 3), showing excellent correspondence of the 11,484 samples (representing 89 seconds of contiguous walking). The Pearson's linear correlation coefficient for the two sets of data was 0.9894 ($P < 0.00001$).

Parameter	-95% CI	Beta	+95% CI
Slope	0.9797	0.9916	1.0034
Constant	-0.0064	0.0080	0.0224

Table 1. Linear regression of stride times, Vicon vs. x-io sensors. $R^2 = 0.9853$, $F(1,404) = 27079$, P (model) = 0.00056

Individual strides from each task were compared directly to one another by comparing the calculated stride times for each ankle (representative data showing the near-perfect fit from the dynamic time warping is shown in Figure 4 and Figure 5). Figure 6 shows that the relationship between stride time as measured by Vicon vs. the gyroscopes is highly linear. The stride times were found to be normally distributed, so they were compared by Pearson's correlation, which showed that they were significantly correlated ($r = 0.9756$, $P < 0.000001$). A linear regression was performed to compare the Vicon stride time data to the gyroscope stride time data, which is shown in Table 1, and the residuals for the regression were normally distributed (Kolmogorov-Smirnov test, $P < 0.00001$). The correspondence is excellent: the line has a slope of approximately 1, and passed through the origin.

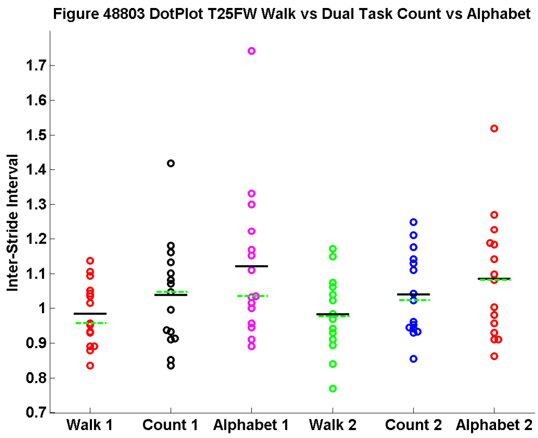

Figure 7. Comparison of stride time values (time between heel-strike). This was determined during T25FW (mean between strides 2-4) when walking at full speed using Xio sensors for the left foot. Black horizontal lines are mean values, light green dashed lines are medians. N =15.

Comparison of Gait during T25FW for Both Dual Tasks

As part of a larger protocol, healthy participants in study two walked the T25FW seven times in the following order: practise (not part of analysis), walking only 1, counting backward 1, alternate alphabet 1, walking only 2, counting backward 2, alternate alphabet 2. By performing all tasks twice, we could inspect if there was a learning effect during our protocol, and whether the results for a given participant were consistent. The values for the stride times are shown in figure 7 (mean values are black horizontal lines, median values are green horizontal lines). Medians were calculated due to one participant having outlier values during the dual tasks. A repeated measures ANOVA showed that there was a significant difference between conditions ($F(5,89) = 5.925$, Probability > F is 0.000127). In a post hoc analysis (Table 2, Matlab, Tukey-Kramer, multcompare) there was a significant difference between either version of the walking-only task vs. either version of the alternate alphabet task, but not between any other tasks (see asterisks). To test for consistency and the possibility of learning effects, we compared the magnitudes of differences between means of identical tasks (e.g. walk 1 vs. walk 2 in Table 2, column 4) vs. differences of non-identical tasks (e.g. walk 1 vs. count 1). The mean1 minus mean2 values of the non-identical tasks ranged from 0.044 to 0.1375 seconds (mean ± S.D. 0.0772 ± 0.0330). The differences in the identical walking-only and counting tasks were 0.0068 and 0.0021 seconds, respectively, which are much smaller and well outside the range of the other differences. By contrast, the difference between the two alternate alphabet tasks was 0.0367 seconds, which was comparable to the non-identical tasks. The mean of the second attempt at the alphabet task was faster than the first attempt, but this did not reach significance ($P = 0.1008$, paired t test).

Subjective Comparison of Both Dual Tasks

When rating how difficult they found the dual task from 0 ("Not at All") to 100 ("Extremely"), the mean was 63.13 ± 21.20 (mean ± S.D.) for the alternate alphabet, vs. 32.50 ± 16.69 for counting backwards by ones ($P = 0.0156$, Wilcoxon Signed Rank test). When rating how much they thought the dual task affected their walking from 0 to 100, the mean was 40.63 ± 19.35 for the alternate alphabet, vs. 28.50 ± 21.80 for counting backwards by ones ($P = 0.0625$, Wilcoxon Signed Rank test). We conclude that subjectively our participants found the alternate alphabet task significantly more difficult, and that there was a trend for their opinion of the effects on walking for the alternate alphabet task to be greater.

DISCUSSION

In this study we set out to compare how two different dual task paradigms known to create cognitive motor interference, counting backward vs. the alternate alphabet, would affect sensor-derived measures of ambulatory function during the T25FW. As expected, we found that the subjectively more difficult task (alternate alphabet) resulted in statistically significant lengthening of stride times (slower cadence) compared to walking alone, while the subjectively easier task (counting backward) did not result in significant lengthening of stride times. Although the alternate alphabet resulted in lengthened stride times compared to counting backwards, these differences were not significant.

Types of Dual Tasks & Cognitive Demands

The literature on multitasking and cognitive motor interference is replete with potential interfering tasks. Of those tasks that are mental, the following categories were suggested in a meta-analysis by Al-Yahya et al., [1] (in order of the tasks' effects on walking speed in healthy volunteers): Mental Tracking (e.g. serial subtraction), Verbal Fluency (e.g. naming animals), Working Memory (counting backwards), Reaction Time, and Discrimination and Decision Making (e.g. Stroop tasks).

It has been suggested that the tasks that have the greatest effects on ambulation are those that are most difficult. For example, when comparing an arithmetic task to a verbal fluency task, while both could increase stride time significantly, only the arithmetic task significantly increased the coefficient of variation of the stride time [6].

Because there are many possible ways of performing a dual task with ambulation [7], consistency among papers is lacking. The most recent attempt at providing dual task guidelines dates from 2006 [11], when the European GAITRite Network Group recommended "commonly used and validated cognitive tasks such as counting backward from 50 out loud, and a verbal fluency task such as enumerating as many animal names as possible." Those guidelines did not comment on how difficult the cognitive task should be, or how the difficulty of the task selected may have a crucial effect on ambulatory metrics.

Tasks that are too easy (e.g. normal counting, i.e. 1,2,3) for a particular cohort will not have a significant effect on walking speed. Tasks that are too difficult may result in the cognitive task being prioritised while walking is neglected [25]. Cognitive task difficulty can be greatly lessened via learning effects during dual task protocols, and with practice of certain tasks, the primary task decrement is minimised or even eliminated [28]. In one study of a variety of interfering tasks including carrying a cup of water, naming animals, serial subtraction by threes, and the alternate alphabet task, virtually all ambulation tasks accelerated slightly due to learning effects when performed one week later [19]. The problem with verbal fluency tasks is that they are not immediately repeatable: repeating the same verbal fluency task twice in a row allows for learning effects, while similar but different verbal fluency tasks (names of animals, countries, vegetables, and fruits) may not be equally difficult [3].

Serial subtraction is comparatively resistant to learning effects and has different levels of difficulty depending on the number selected (e.g. counting backward by twos, by tens, by fives, by threes and by sevens), and these differences in difficulty are associated with greater physical performance decrements in dual tasks [32]. Walking has been investigated with dual tasks using a range of different numbers for serial subtraction [27]. Among the elderly, the cognitively impaired have a slower baseline walk and are slowed more by serial subtractions of twos and by verbal fluency tests [29]. By contrast, counting backward from 50 (i.e. 50, 49, 48) is a fairly easy task that may affect only cognitively-challenged cohorts such as patients with frontal lobe dysfunction [2].

Recommendations for Guidelines

Although targeting anti-fall interventions to high risk individuals reduces morbidity, non-selective anti-fall exercise intervention programmes for all elderly do not reduce morbidity [10]. Thus, recognising high risk patients is essential. Frailty is a high risk health state related to the ageing process in which a person is at a higher risk of a sudden, radical deterioration in their overall physical and mental health status after an apparently small-scale health challenge, such as a minor fall in the home; approximately 10% of individuals over 65 years old are thought to meet the criteria for frailty, and the percentages are much higher for individuals over 85 years [9]. In the current guidelines to detect frailty in community dwelling older adults from the British Geriatrics Society, Age UK and the Royal College of General Practitioners (UK), the recommended assessment for frailty in community and outpatient settings may be indicated by a gait speed <0.8m/s; a timed-up-and-go test >10s; or a score of ≥ 3 on the PRISMA 7 frailty questionnaire; any can indicate frailty [31], as can the patient's history of falls.

Group 1	Group 2	-95% CI	Mean1 - Mean2	+95% CI	
Walk 1	Count 1	-0.1452	-0.0547	0.0358	
Walk 1	Alphabet 1	-0.2280	-0.1375	-0.0470	*
Walk 1	Walk 2	-0.0973	-0.0068	0.0838	
Walk 1	Count 2	-0.1473	-0.0568	0.0338	
Walk 1	Alphabet 2	-0.1913	-0.1008	-0.0103	*
Count 1	Alphabet 1	-0.1733	-0.0828	0.0077	
Count 1	Walk 2	-0.0426	0.0479	0.1384	
Count 1	Count 2	-0.0926	-0.0021	0.0884	
Count 1	Alphabet 2	-0.1366	-0.0461	0.0444	
Alphabet 1	Walk 2	0.0402	0.1307	0.2213	*
Alphabet 1	Count 2	-0.0098	0.0807	0.1713	
Alphabet 1	Alphabet 2	-0.0538	0.0367	0.1272	
Walk 2	Count 2	-0.1405	-0.0500	0.0405	
Walk 2	Alphabet 2	-0.1845	-0.0940	-0.0035	*
Count 2	Alphabet 2	-0.1345	-0.0440	0.0465	

Table 2. Tukey-Kramer post hoc comparison of stride time values (time between heel-strike). This was determined at full speed during T25FW (mean between strides 2-4) using X-io sensors for the left foot. Asterisks in column 6 denote a significant difference $\alpha = 0.05$. N =15.

In the current study, we compared two cognitive tasks that have different levels of subjective difficulty. For future guidelines for using the dual task, a specific difficulty should be sought. If the goal is to recognise fallers, then a cognitive task should be chosen where healthy volunteers are able to perform the dual task while walking quickly. For example, serial subtraction has been shown to have a significantly higher cognitive cost in stroke patients than in young healthy adults [24], making it potentially useful as an indicator of fall risk.

CONCLUSIONS

From this study's results, we conclude: 1) the x-io sensors make valid measurements of angular velocity during walking, 2) the x-io sensors when combined with DTW make valid measures of heel strike times and stride times, 3) according to both gait and subjective measures, the alternate letter alphabet task interferes with walking rate during the T25FW consistently and significantly, and that this interference is more reliable than for counting backward by ones. This implies that mental tracking in a dual task strongly interferes with walking [36; 13]. One potential limitation is that the alternate alphabet task may be subject to learning effects, although this is not significant for two performances of the task. The implications are that ambulatory performance decrement from the dual task depends upon the specific cognitive task and on its difficulty. Future meta-analyses on the value of detecting fall risk via the dual task paradigm should be based on a single version of the dual task paradigm, rather than combining results from studies with different tasks. Future guidelines for dual tasks will have to be quite proscriptive to result in consistent results between studies; this includes how prioritisation instructions are given as well as cognitive task selection and difficulty.

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REFERENCES

1. Al-Yahya, E., Dawes, H., Smith, L., Dennis, A., Howells, K., & Cockburn, J. (2011). Cognitive motor interference while walking: a systematic review and meta-analysis. *Neuroscience & Biobehavioral Reviews*, 35(3), 715-728.
2. Allali, G., Kressig, R. W., Assal, F., Herrmann, F. R., Dubost, V., & Beauchet, O. (2007). Changes in gait while backward counting in demented older adults with frontal lobe dysfunction. *Gait & Posture*, 26(4), 572-576.
3. Barry, D., Bates, M. E., & Labouvie, E. (2008). FAS and CFL forms of verbal fluency differ in difficulty: a meta-analytic study. *Applied Neuropsychology*, 15(2), 97-106.
4. Barth, J., Oberndorfer, C., Pasluosta, C., Schülein, S., Gassner, H., Reinfelder, S., Kugler, P., Schuldhaus, D., Winkler, J., Klucken, J. & Eskofier, B. M. (2015). Stride segmentation during free walk movements using multi-dimensional subsequence dynamic time warping on inertial sensor data. *Sensors*, 15(3), 6419-6440.
5. Beauchet, O., Dubost, V., Herrmann, F. R., & Kressig, R. W. (2005a). Stride-to-stride variability while backward counting among healthy young adults. *Journal of Neuroengineering & Rehabilitation*, 2(1), 26.
6. Beauchet, O., Dubost, V., Aminian, K., Gonthier, R., & Kressig, R. W. (2005b). Dual-task-related gait changes in the elderly: does the type of cognitive task matter? *Journal of Motor Behavior*, 37(4), 259.
7. Beauchet, O., Annweiler, C., Dubost, V., Allali, G., Kressig, R. W., Bridenbaugh, S., Berrut, G., Assal, F., & Herrmann, F. R. (2009). Stops walking when talking: a predictor of falls in older adults? *European Journal of Neurology*, 16(7), 786-795.
8. Brandler, T. C., Oh-Park, M., Wang, C., Holtzer, R., & Verghese, J. (2012). Walking while talking: Investigation of alternate forms. *Gait & Posture*, 35(1), 164-166.
9. British Geriatrics Society, Royal College of General Practitioners, Age UK (2014). *Fit for Frailty: Consensus best practice guidance for the care of older people living with frailty in community and outpatient settings*. London: British Geriatrics Society.
10. Feder, G., Cryer, C., Donovan, S., & Carter, Y. (2000). Guidelines for the prevention of falls in people over 65. *British Medical Journal*, 321(7267), 1007.
11. Kressig, R. W., & Beauchet, O. (2006). Guidelines for clinical applications of spatio-temporal gait analysis in older adults. *Aging Clinical and Experimental Research*, 18(2), 174-176.
12. Leardini, A., Sawacha, Z., Paolini, G., Ingrosso, S., Nativo, R., & Benedetti, M. G. (2007). A new anatomically based protocol for gait analysis in children. *Gait & Posture*, 26(4), 560-571.
13. Learmonth, Y. C., Sandroff, B. M., Pilutti, L. A., Klaren, R. E., Ensari, I., Riskin, B. J., Holtzer, R. & Motl, R. W. (2014). Cognitive motor interference during walking in multiple sclerosis using an alternate-letter alphabet task. *Archives of Physical Medicine and Rehabilitation*, 95(8), 1498-1503.
14. Lundin-Olsson, L., Nyberg, L., & Gustafson, Y. (1997). "Stops walking when talking" as a predictor of falls in elderly people. *The Lancet*, 349(9052), 617.

15. Madgwick, S. (2010a). An efficient orientation filter for inertial and inertial/magnetic sensor arrays. Report x-io and University of Bristol (UK).
16. Madgwick, S. O. (2010b). Automated calibration of an accelerometers, magnetometers and gyroscopes-a feasibility study. Technical Report from X-io. http://x-io.co.uk/res/doc/ automated_calibration_feasibility_study.pdf.
17. Madgwick, S. O., Harrison, A. J., & Vaidyanathan, R. (2011). Estimation of IMU and MARG orientation using a gradient descent algorithm. In *2011 IEEE International Conference on Rehabilitation Robotics* (pp. 1-7). IEEE.
18. Menant, J. C., Schoene, D., Sarofim, M., & Lord, S. R. (2014). Single and dual task tests of gait speed are equivalent in the prediction of falls in older people: a systematic review and meta-analysis. *Ageing Research Reviews*, 16, 83-104.
19. Muhaidat, J., Kerr, A., Evans, J. J., & Skelton, D. A. (2013). The test–retest reliability of gait-related dual task performance in community-dwelling fallers and non-fallers. *Gait & Posture*, 38(1), 43-50.
20. Needham, R., Naemi, R., & Chockalingam, N. (2014). Quantifying lumbar–pelvis coordination during gait using a modified vector coding technique. *Journal of Biomechanics*, 47(5), 1020-1026.
21. Needham, R., Naemi, R., Healy, A., & Chockalingam, N. (2015). Multi-segment kinematic model to assess three-dimensional movement of the spine and back during gait. *Prosthetics and Orthotics International*, 0309364615579319.
22. Nilsagård, Y., Carling, A., & Forsberg, A. (2012). Activities-specific balance confidence in people with multiple sclerosis. *Multiple Sclerosis International*, 2012, Article 613925.
23. North, R. A. (1977, October). Task functional demands as factors in dual-task performance. In *Proceedings of the Human Factors Society Annual Meeting* (Vol. 21, No. 5, pp. 367-371). Sage CA: Los Angeles, CA: SAGE Publications.
24. Patel P, Bhatt T. (2014). Task matters: influence of different cognitive tasks on cognitive-motor interference during dual-task walking in chronic stroke survivors. *Top. Stroke Rehabil.*; 21: 347–357.
25. Patel, P., Lamar, M., & Bhatt, T. (2014b). Effect of type of cognitive task and walking speed on cognitive-motor interference during dual-task walking. *Neuroscience*, 260, 140-148.
26. Plummer-D'Amato P, Altmann LJ, Saracino D, Fox E, Behrman AL, Marsiske M. (2008). Interactions between cognitive tasks and gait after stroke: a dual task study. *Gait & Posture*; 27: 683–688.
27. Smith, E., Cusack, T., & Blake, C. (2016). The effect of a dual task on gait speed in community dwelling older adults: A systematic review and meta-analysis. *Gait & Posture*, 44, 250-258.
28. Strobach, T., Liepelt, R., Pashler, H., Frensch, P. A., & Schubert, T. (2013). Effects of extensive dual-task practice on processing stages in simultaneous choice tasks. *Attention, Perception, & Psychophysics*, 75(5), 900-920.
29. Theill, N., Martin, M., Schumacher, V., Bridenbaugh, S. A., & Kressig, R. W. (2011). Simultaneously measuring gait and cognitive performance in cognitively healthy and cognitively impaired older adults: The Basel motor–cognition dual‐task paradigm. *Journal of the American Geriatrics Society*, 59(6), 1012-1018.
30. Turetsky, R. J., & Ellis, D. P. (2003). Ground-truth transcriptions of real music from force-aligned MIDI syntheses. In *4th International Conference on Music Information Retrieval*, Baltimore, USA.
31. Turner, G., & Clegg, A. (2014). Best practice guidelines for the management of frailty: a British Geriatrics Society, Age UK and Royal College of General Practitioners report. *Age and Ageing*, 43(6), 744-747.
32. Vaportzis, E., Georgiou-Karistianis, N., & Stout, J. C. (2014). Age and task difficulty differences in dual tasking using circle tracing and serial subtraction tasks. *Aging Clinical and Experimental Research*, 26(2), 201-211.
33. Van Der Slikke, R. M. A., Berger, M. A. M., Bregman, D. J. J., Lagerberg, A. H., & Veeger, H. E. J. (2015). Opportunities for measuring wheelchair kinematics in match settings; reliability of a three inertial sensor configuration. *Journal of Biomechanics*, 48(12), 3398-3405.
34. Verghese, J., Buschke, H., Viola, L., Katz, M., Hall, C., Kuslansky, G., & Lipton, R. (2002). Validity of divided attention tasks in predicting falls in older individuals: a preliminary study. *Journal of the American Geriatrics Society*, 50(9), 1572-1576.
35. Wajda, D. A., Motl, R. W., & Sosnoff, J. J. (2013). Dual task cost of walking is related to fall risk in persons with multiple sclerosis. *Journal of the Neurological Sciences*, 335(1), 160-163.
36. Wickens, C. D. (2008). Multiple resources and mental workload. *Human Factors*, 50(3), 449-455.
37. Yang, L., He, C., & Pang, M. Y. C. (2016). Reliability and validity of dual-task mobility assessments in people with chronic stroke. *PloS One*, 11(1), e0147833.